Non-Invasive Blood Sugar Measuring Tool Using Arduino-Based Linear Regression Method

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Abstract: Diabetes Mellitus is a disease characterized by high blood sugar levels caused by decreased production or function of the hormone insulin in the body. Traditional tests are usually invasive, involving skin puncture to obtain a blood sample, which can be unsuitable for some sufferers. Non-invasive methods provide a viable alternative for monitoring blood sugar levels. This research aims to create an Arduino-based non-invasive blood sugar level measuring device, leveraging the optical property of laser absorption in liquid media, detected by a photodiode sensor. The primary objective is to develop a device that accurately measures blood sugar levels without the need for invasive procedures. The photodiode sensor outputs voltage, which is then converted into blood sugar level (mg/dl) using a linear regression equation. The derived linear regression equation is y = 31.401 + 36.002x, with a previously obtained correlation value of 0.971 between voltage and blood sugar levels at a significance level of 0.01. The average error value (errata) of this device is 0.0905. The smallest measurement error was observed in patients C and Q, at 0.01 or approximately 1%, while the largest error was in patient L, at 0.22 or around 22%. The contributions of this research include the development of a non-invasive, accurate, and cost-effective method for blood sugar monitoring, potentially improving patient compliance and comfort.

Keywords: Blood Sugar, Diabetes Mellitus, Linear Regression, Non-Invasive, Photodiode Sensor.

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Introduction

Diabetes Mellitus is a form of health disorder in the form of symptoms that arise due to increased blood sugar levels due to insulin resistance and metabolic problems (Toharin et al., 2015). Blood sugar levels are also called blood glucose. Glucose is the end product of carbohydrate metabolism and is the main energy source for living organisms. There are three types of blood sugar levels in a person's body, namely normal, hypoglycemia and hyperglycemia. Hypoglycemia is a condition where blood sugar levels decrease due to food intake with unbalanced nutrition or blood containing a lot of insulin. Hyperglycemia is a condition where blood sugar levels increase due to insufficient insulin in the body, this condition is known as diabetes mellitus. The reference value for blood sugar levels for 8 hours of fasting is 70-110 mg/dl, blood sugar levels for two hours post prandial (after eating) are ≤ 140 mg/dl, and blood sugar at any time is ≥110 mg/dl (Siregar et al., 2020).

Hyperglycemia in diabetes sufferers that is not well controlled will trigger serious damage to the body's systems, especially blood vessels and nerves (Kusnanto et al., 2019). Diabetes Mellitus is a disease that must be monitored regularly by carrying out regular examinations. The usual way to check blood sugar levels is by using an invasive method (injuring the skin). Invasive methods are used for laboratory checks and the use of glucometers. However, people with type 2 diabetes mellitus should not be injured because it is feared that the wound will widen and be difficult to dry and could lead to amputation (Puspita, 2019). Apart from that, there are some people who are afraid to check their blood sugar levels invasively because they suffer from a phobia of blood and needles. Therefore, as an alternative, a non-invasive means of checking blood sugar levels is needed, namely a way of checking without having to injure the patient's body. Some research have studied the non-invasive blood measurement such as glucose measurement based on near-infrared spectroscopy (Shulei et al., 2017; Bader & Jarjees, 2023), glucose molar absorptivity (Truong et al., 2022) and electromagnetic properties of glucose in blood (Sreenivas & Laha, 2019) .

In recent years, research has been carried out regarding the manufacture of non-invasive blood sugar checking devices. The research entitled " Towards the Portability of a Capacitive-sensor based Non-invasive Glucometer: A Simulation Approach" uses capacitor and operational amplifier (opamp) (Rahamoni et al., 2020). The next research analyzes blood sugar levels (blood glucose) based on the temperature difference between the tagus and antihelix as measured using the LM35 sensor. This research is non-invasive and the error rate obtained is 1-15% (Kemalasari & Purnomo, 2011). While innovative in using temperature difference, this method may be influenced by external temperature variations and lacks integration with modern microcontroller technology for improved accuracy and usability. Another study analyzes the voltage spectrum using near-infrared on a blood glucose level detector. In this study, the voltage spectrum values obtained were most accurate at 1 second and 1.7 seconds with a correlation value of -0.9755073445. Blood sugar levels are checked by inserting a finger and pressing a push button, the OPT101 sensor is read, resulting in an ADC value, which is then calculated into a voltage value. The average measurement error value using this tool with the highest correlation value is 1.659% (Nugroho et al., 2021). This research emphasizes the voltage spectrum but does not consider user interface and real-time data logging.

Another research related to non-invasive measurement of sugar levels is the creation of a detector to measure blood glucose using near-infrared. This research utilized infrared photodiodes and LEDs. The minimum measurement results from three patient samples by comparing invasive methods with non-invasive methods showed a range of sensor readings with corresponding blood glucose levels. However, this research has not used a data logger to store test data automatically and patient samples in testing have not varied significantly (L. V. Santoso, 2018). While this study uses infrared technology, it lacks automated data storage and diverse sample testing.

Based on these studies, further research is needed to address the limitations identified, including the need for automated data logging, diverse sample testing, and real-time monitoring interfaces. This research designs and creates a tool that can determine blood sugar levels quickly, accurately, and without injuring the patient's skin. The aim of the research is to design and implement a non-invasive blood sugar measuring device based on Arduino Nano using the linear regression method. The non-invasive method used in this research leverages the laser absorption properties of liquid media, specifically blood in the patient's finger. The significant improvements and contributions of this research include providing quick and accurate measurements using a linear regression equation derived from the correlation between voltage and blood sugar levels. Moreover, patient data is input via a custom Android application and stored on a Micro SD card, eliminating manual recording and enabling easy data retrieval through a laptop or computer. Additionally, results are displayed on an I2C 16x2 LCD, making it easy for patients and healthcare providers to read and interpret the data. These advancements address the limitations of previous studies by incorporating modern microcontroller technology, enhancing accuracy through linear regression, and providing a seamless and efficient user experience with automated data management and real-time display of results.

In this study, Pearson Correlation are implemented to analyse correlation between blood sugar and voltage. Pearson Correlation has been widely used in many filed such as Movement Patterns Based on Electroencephalograph Signals (Maulana et al., 2023), estimation of blood pressure (Colmán et al., 2022), power analysis of digital multimeter (Kundrata et al., 2020) and in gates of logic circuits (Shi et al., 2024). Pearson Correlation and linear regression were taken from patients aged around 20 years in the morning with the condition that they were not allowed to eat beforehand to obtain eight-hour fasting glucose. Age is one of the factors that influences the increase in blood sugar (Listyarini et al., 2022). Therefore, so that the data used for Pearson Correlation and linear regression calculations are homogeneous and avoid large errors, samples were taken from patients of almost the same age, around 20 years of age. Then taking fasting glucose also has the same reason, namely to avoid large errors because if data is taken at any time then the food consumed by the patient cannot be controlled. After the regression equation is obtained, it will be entered into the coding and the units will be changed to mg/dl. Once the device is ready to use, it can test patients of any age and any condition, whether fasting or after eating.

The photodiode sensor is used as a voltage value reader for light intensity which will be compared with the results of the glucometer reading. The glucometer was used as a reference or standard in this research. The first test was carried out to determine the relationship between voltage (V) and blood sugar levels (mg/dl) through calculating the correlation coefficient via SPSS. If the relationship between the two variables is strong, proceed with linear regression calculations to find the equation for voltage (V) and blood sugar levels (mg/dl). The regression equation will be entered into the coding so that the output from the tool is blood sugar levels in mg/dl units.

Research Method

The initial stage in making a non-invasive blood sugar measuring device is to study various references and theories related to this research. This was done to analyze the advantages and disadvantages of previous research. The next stages are hardware design, software design, tool assembly, sample testing and data analysis.

Hardware Design

Hardware design begins by creating a circuit schematic using KiCad software, which is shown in Figure 1.

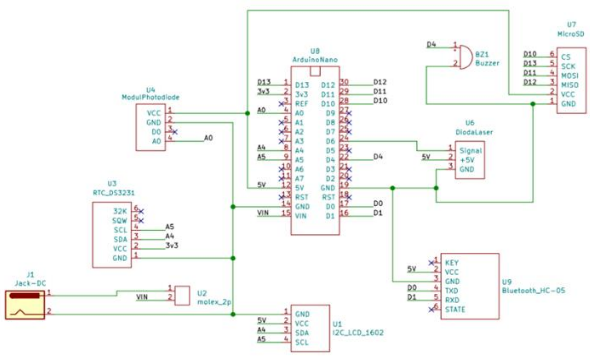

Figure 1 Circuit schematic

The components needed to design this non-invasive blood sugar level measuring device include Arduino Nano, photodiode sensor module, laser diode, RTC DS3231, Bluetooth HC-05 module, microSD module, SD Card, 16x2 I2C LCD, and switch.

Figure 2 shows an overview of how the system for measuring blood sugar levels non-invasively works. The RTC DS3231 as a digital timer aims to determine the time when collecting voltage and blood sugar level data in real time. The switch aims to activate or start the system. Bluetooth HC-05 is used as a slave or receiver on Arduino. Bluetooth HC-05 is used for wireless communication by converting the serial port to Bluetooth. Bluetooth HC-05 works on radio waves with a frequency of 2.4 GHz with Bluetooth V2.0 + EDR (Enhanced Data Rate) 3 Mbps modulation type (Zainuri et al., 2015).

The laser diode will emit a light source that penetrates the finger and the light intensity will be captured by a photodiode sensor in the form of a voltage ranging from 0-5 volts. Arduino Nano has a function as a data processor which will be calculated into blood sugar level values. The output from the tool, namely the value of blood sugar levels (mg/dl), will appear on the 16x2 LCD and will be saved on the SD card. The function of the microSD module is to be a means of communication between the Arduino nano and the SD card. In this research, the SD card functions as a data logger which has the advantage of using simpler infrastructure compared to a database or EEPROM and also having large data storage space (Pauzan & Yanti, 2022).

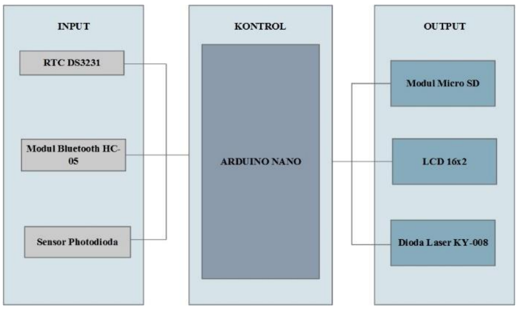

Figure 2 Block diagram

Software Design

In this study, the process of inputting patient identity was via an Android application with Bluetooth HC-05 communication. Making applications on Android using MIT App Inventor. MIT App Inventor is a system for creating website-based Android applications (Pauzan & Yanti, 2021) which has been widely used for IoT (Munasinghe et al., 2019), robot (Sajimon et al., 2023) and data acquisition (Bouraiou et al., 2023). Making applications in MIT App Inventor uses code blocks with various layouts.

The first stage in creating an application in MIT App Inventor is to go to ai2.appinventor.mit.edu. On this website there are two main pages, namely the designer page and the blocks page. The application design process is on the designer page, followed by creating code blocks by drag and drop. After the application has been created, to install the application on the handphone, build the Android App (.apk) by writing 6 characters code or scanning the QR code in the MIT AI2 Companion which was previously installed on the handphone. Images of the application and code blocks are shown in Figure 3 and Figure 4 respectively.

Figure 3 Mobile application

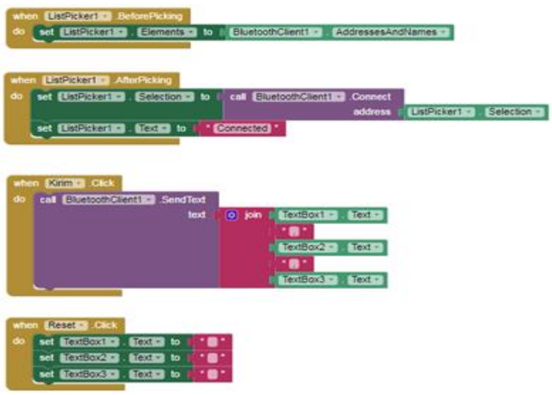

Figure 4 Code blocks created in MIT App Inventor

Figure 4 shows the code blocks used in building applications on Android. The meaning of these code blocks is that before entering the patient's identity in TextBox1, TextBox2, and TextBox3, Bluetooth must be connected first by pressing the "check Bluetooth connection" button and selecting the appropriate Bluetooth. Once connected, the next step is to enter patient data into the application. The data entered in this application will be sent to the Arduino Nano as input data which will appear on the LCD and is also stored on the SD card.

Other software used is SPSS (Statistical Package for the Social Sciences) and Arduino IDE (Integrate Development Environment). SPSS is used to calculate the correlation value between voltage (V) and blood sugar levels (mg/dl). If the correlation is declared strong or very strong, then continue by calculating linear regression with SPSS (Kereh et al., 2015). Arduino IDE is software used to write program code, compile and upload it into memory on the microcontroller. The three parts in the Arduino IDE include the program editor, compiler, and uploader (Amestica et al., 2019).

Tool Assembly

Tool assembly is preceded by circuit schematic design, footprint creation, PCB design, PCB printing, and 3-dimensional casing creation. Figure 5 shows a blood sugar measuring device consisting of a PCB holder and a location for scanning fingers.

Figure 5 Non-invasive blood sugar level measuring tool using the linear regression method

The grey casing is where the PCB is, while the black is where the finger scanner is located which contains the laser diode and photodiode sensor.

Sample Testing

In this study, the first test aims to find the correlation coefficient value by comparing the voltage value (V) with blood sugar levels (mg/dl). If the relationship is strong then continue by looking for the liner regression value and then carry out a second test, namely comparing the blood sugar level value (mg/dl) from the tool with a glucometer as a reference. This aims to see the performance and accuracy of the tool. The brand of glucometer used is Sinoheart which has specifications as shown in Table 1.

Table 1 Sinoheart brand glucometer specifications

Specification	Description
Blood volume	0.6 μl
Sample type	Capillary whole blood, venous blood
Measurement time	10 $\pm$ 1 s
Storage temperature	-20^{o}C to 55^{o}C

Dimensions	96x55x18 mm
Heavy	About 40 g
Resource	Battery CR2032
Operating voltage	3V
Current	10 mA
Memory	200 blood glucose test results
Operating conditions	10^{o}C to 35^{o}C and ≤ 80%RH
Units of measurement	mg/dl or mmol/l
Measuring range	20 to 600 mg/dl or 1.1 to 33.3 mmol/l

The bivariate correlation coefficient formula between variables x and y is shown by equation (1). The x variable is the voltage (V) from the device while the y variable shows the blood sugar level (mg/dl) from the glucometer.

$$r = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2}\sqrt{n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2}} \quad (1)$$

where r is the correlation coefficient and the sigma sign (Σ) explains that the calculation runs from $i = 1$ to n with the addition operation, with n being the total samples tested. The strength of the correlation relationship is shown in Table 2 (Kereh et al., 2015).

Table 2 The Strength of Correlation Relationships

r	**Description**
0	There is no relationship
0.01 – 0.20	Very weak or low
0.21 – 0.40	Weak or low
0.41 – 0.60	Enough
0.61 – 0.80	Tall or strong
0.81 – 0.99	Very strong or very high
1	Perfect

The correlation coefficient (r) value can be positive or negative (Safitri, 2016). This sign describes the direction of the relationship of the related variables. If the correlation coefficient value has a positive sign ($0 \le r \le 1$), it indicates that the relationship between variables is directly proportional, that is, when the value of the independent variable increases, the value of the dependent variable will increase, and vice versa, when the independent variable decreases, the independent variable also decreases. Meanwhile, if the correlation coefficient value has a negative sign, namely $-1 \le r \le 0$, it means that the relationship between these variables is inversely proportional, that is, when the value of the independent variable increases, the value of the dependent variable will decrease, and vice versa, when the value of the independent variable decreases, the value of the dependent variable will increase.

There are two types of regression, namely simple regression and multiple regression. Simple regression is regression for one independent variable with one dependent variable, while multiple regression is regression for more than one independent variable with one dependent variable (Farjana et al., 2021; Zhao et al., 2020). This research uses a simple regression form because it only involves one independent variable, namely voltage (V), and a dependent variable, namely blood sugar levels (mg/dl). Mathematically, simple regression is shown by equation (2).

$$y = a + bx \tag{2}$$

Where y is the dependent or dependent variable, x is the independent variable, a is the equation constant or intercept, and b is the direction coefficient or beta coefficient.

Data Analysis

This stage contains the analysis process of the data that has been obtained from sample testing. In this research, there are several types of data analysis. First, namely analyzing the relationship between voltage (V) and blood sugar levels (mg/dl). This first analysis will produce correlation coefficients and linear regression equations. Second, namely analyzing the accuracy of the blood sugar level data (mg/dl) obtained from the tool and comparing it with the blood sugar level (mg/dl) obtained from the glucometer. To see the accuracy of a measurement, you can see the discrepancy value or measurement error.

The discrepancy (Z) between two values of the same physical quantity, for example ($X \pm \Delta X$) and ($Y \pm \Delta Y$), with Y as the standard or reference value of the calibrated instrument, is mathematically written as (3) (Pandiangan & Arkundato, 2018).

$$Z = \left|\frac{X - Y}{Y}\right| \times 100\% \tag{3}$$

with Z referred to as the measurement error value. If the Z value obtained is very small, it can be concluded that the measurement results are considered very good. Accuracy shows the level of quality of measurements made on measurements from calibrated or standard (reference) tools.

Result and Discussion

The main concept in this research is the use of laser absorption properties of liquid media, in this case the patient's blood. Therefore, the tool created can collect data on patient sugar levels (mg/dl) non-invasively without injuring the patient's fingers with a needle. The signal detected by the photodiode sensor is an analog signal which will then be converted to digital via the ADC pin on the Arduino Nano (Pauzan & Yanti, 2019). In principle, the processes that occur in an ADC (Analog to Digital Converter) include sampling, quantization and coding. Sampling is collecting data at a certain point in time. The more sampling points at the same time, the more accurate the digital data produced. This accuracy is expressed in the number of bits of the ADC. For example, the Arduino Nano has a 10bit ADC, which means it can produce digital values ranging from 0-1023 from the conversion of analogue values which are input data. Quantization is the process of mapping input into digital quantities, while coding is the process of producing digital values from the previous process (quantization). The data that will be displayed on the I2C 16x2 LCD and stored on the SD card is a digital signal given by the Arduino nano to the LCD and SD card.

Blood sugar data was collected using a glucometer twice. First, namely to find the relationship between the voltage in volts from the device and blood sugar in mg/dl from the glucometer from which the correlation coefficient value and linear regression equation will be calculated. Second, it is carried out for reference data when the tool that has been created is accompanied by a linear regression equation that has been obtained in coding. The second aim of collecting blood sugar level data with a glucometer is to validate the blood sugar level measuring tool that has been made. Blood sampling using a glucometer for the first and second tests was carried out once for each patient for a total of 20 patients.

The Relationship of Voltage with Blood Sugar Levels

Voltage (V) data collection from 20 patients was carried out at the same time as blood sugar level data collection (mg/dl) from a glucometer. This is because blood sugar levels can easily change due to several factors. Voltage (V) data was taken 20 times for each sample with the data collection time for each patient taking 10 seconds so that 1 time of voltage (V) data took 0.5 seconds. Figure 5 shows the activity of collecting tension data from the patient's hand using the tool that has been made. Table 3 shows the data obtained from the device in the form of voltage (V) and the glucometer in the form of blood sugar levels (mg/dl).

Table 3 Comparison of Voltage with Blood Sugar Levels

No.	Patient	Average voltage (V)	Level Blood Sugar (mg/dl)
1	A	1.56	86
2	B	1.83	101
3	C	1.52	88
4	D	1.43	81
5	E	1.55	93
6	F	1.65	84

7	G	0.06	31
8	H	1.71	99
9	I	1.64	88
10	J	2.18	107
11	K	1.77	93
12	L	1.47	85
13	M	2.07	101
14	N	1.43	81
15	O	1.55	87
16	P	1.46	88
17	Q	1.60	88
18	R	1.55	93
19	S	1.41	82
20	T	1.53	87

Based on Table 3, 19 patients had normal blood sugar (glucose) levels while 1 patient had low blood sugar levels, namely 31 mg/dl. All patients whose blood sugar levels were taken using a glucometer for the first test were almost the same age, namely around 20 years old. Age is one of the factors that can influence the increase in blood sugar levels (Listyarini et al., 2022). Therefore, so that the data used for Pearson Correlation and linear regression calculations are homogeneous and avoid large errors, the tests were carried out on patients of almost the same age. The average voltage obtained was between 1 V and 2 V for 17 patients or 85% of the total patients. Meanwhile, those with an average voltage value above 2 V were 2 patients or 10% of the total patients and those with an average voltage below 1 V, namely 0.06 V, were only 1 patient, namely 5% of the total patients.

Data on average voltage and blood sugar levels were compared and analyzed using SPSS to calculate the correlation coefficient. Based on the results of calculations via SPSS, a correlation coefficient value of 0.971 was obtained, which has a very strong correlation relationship in accordance with Table 1 regarding the strength of the correlation relationship. The resulting significance level is 0.01 (1%), meaning the error is only 1% and the accuracy level of the analysis results reaches 99%.

When testing a hypothesis, a significance value will appear. There are two types of significance, namely 1-tailed and 2-tailed. 1-tailed significance is usually used for previously known hypotheses or hypotheses whose direction is already known to be positive or negative and for types of 1-tailed testing. 2-tailed significance is used for hypotheses that are not yet known whether the direction is positive or negative and for 2-tailed tests. The use of 1-tailed is not only to find out the relationship between the two variables but goes further than that, namely proving the negative or positive direction of the relationship between the two variables, whereas if the goal is to see whether or not there is a correlation or relationship between the two variables being tested, you can use 2-tailed. Therefore, in this study the type of significance used is 2-tailed.

In this study, variable x shows voltage (V) and variable y shows blood sugar levels (mg/dl). In statistics, Ho will be rejected if the significance value is less than 0.05 (Utami, 2019; Mariana & Zubaidah, 2015; G. Santoso et al., 2018). The results of the correlation calculation above show that the sig (2-tailed) value obtained is 0.000, so the hypothesis Ho (variables x and y have no relationship) is rejected and Ha (variables x and y have a relationship) is accepted. Based on these results, there is a very significant correlation or relationship between the voltage variable (V) and the blood sugar level variable (mg/dl).

Based on the correlation output obtained from SPSS there are two asterisks (**). This sign illustrates the very strong correlation of these two variables. Two stars (**) means the significance level obtained is 1% while one star (*) indicates a significance level of 5% (Rohmaniyah, 2014). However, if there is no asterisk in the test results, it means there is no relationship or correlation between the variables involved in the test.

The correlation coefficient (r) value can be positive or negative. The range of correlation coefficient values is $-1 \leq r \leq 1$. If $-1 \leq r \leq 0$ then the two variables have an inversely proportional relationship, whereas if 0≤r≤1 then the two variables have a directly proportional relationship. The correlation coefficient (r) value obtained in this study is positive. The negative sign on the coefficient value describes the direction of the correlation or relationship which is directly proportional (unidirectional), namely the higher the voltage value (V), the higher the blood sugar level value (mg/dl) obtained, conversely the lower the voltage value (V), the higher the blood sugar level (mg/dl). Blood sugar (mg/dl) also gets lower.

After knowing that the correlation coefficient obtained has a very strong relationship, the next step is to look for the linear regression equation. The linear regression equation shows the relationship between the two variables mathematically. In this research, the regression analysis used is simple linear regression. Simple linear regression analysis is used to test or predict the influence of one independent variable on one dependent variable and to determine the linearity between the dependent variable and the independent variable. In this research, the data used to find the linear regression equation is using the same data when calculating the correlation coefficient, namely the data in Table 2. The linear regression equation is searched using SPSS software.

The linear regression equation from SPSS output is shown by (4).

$$y = 31.401 + 36.002x \quad (4)$$

where y is blood sugar level (mg/dl), x is voltage (V) and 31.401 is a constant. The graph of (4) is shown in Figure 6.

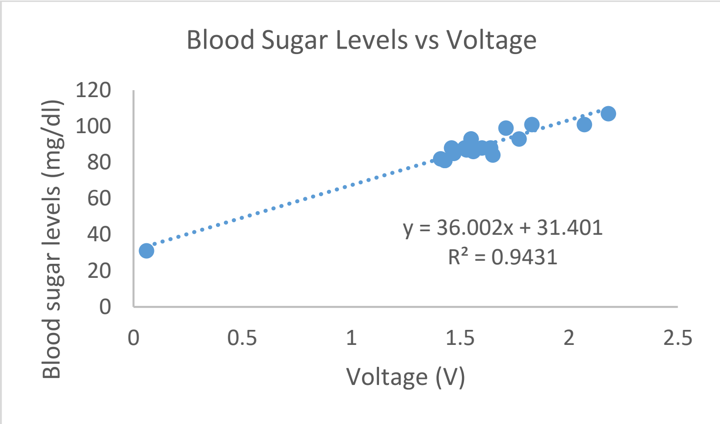

Figure 6 The Relationship between Voltage and Blood Sugar Levels

In Figure 6 the graph formed is a straight line in the same direction as the correlation coefficient value obtained previously. In the graph you can see that there is a point that is far below but still on track. This data is data from patient G who has a blood sugar level of 31 mg/dl and a voltage of 0.06 V. In Figure 6 the linear regression equation is written as in (4) and R^2 (Rsquare) as the coefficient of determination. R^2 functions to predict the magnitude of the contribution of the independent variable (voltage (V)) to the dependent variable (blood sugar level (mg/dl)) simultaneously. The R^2 value obtained is 0.9431 or 94.31%. This value is the square value of the correlation coefficient that has been obtained. Therefore the physical meaning of R^2 is similar to the correlation coefficient. The coefficient of determination value shows that the voltage variable (V) influences the blood sugar level variable (mg/dl) by 94.31%, while the percentage of 5.69% is influenced by variables or factors that were not examined in this study or that are not related. with the variables in the regression equation.

In the SPSS output, apart from obtaining the regression equation, output data or other information is also obtained. Unstandardized Coefficients from Constants is a regression constant which is denoted by a in accordance with (2), which means that if there is no change in the variable x (voltage) then the blood sugar level value will not change or will have a constant value, namely 31.401. The Unstandardize Coefficients of the voltage variable describe the condition that when the voltage (V) increases by 1 unit, blood sugar levels will also increase by 36.002. Standard Error (Constant) shows the error of the constant in the regression equation of 3.332. Standard Error of the stress variable shows the error of the regression coefficient of the stress variable. The meaning of this error is that the smaller the error or error produced, the more important the contribution of voltage (V) to blood sugar levels (mg/dl) of 2.085.

Apart from describing the linear regression equation, SPSS output also displays the t test and significance test. These two outputs are used to see the level of influence of variable x (voltage) on variable y (blood sugar levels). The t test is used to test hypotheses by comparing the t value from statistical calculations with the t table value in the table. If the calculated t value is smaller than the t table value, then variable x has no influence on variable y and vice versa (Andi et al., 2017).

Because this research uses a two-way hypothesis, the significance level used is 1% or 0.01 according to the results of the correlation test. The t table value obtained is 2.878. Based on the linear regression output, the calculated t is greater than the t table, which shows that Ho is rejected and the alternative hypothesis (Ha) is accepted.

Comparison of Blood Sugar Levels on Tools and Glucometers

After the linear regression equation is obtained, the equation is then entered into the coding of the blood sugar detection tool to produce the output of the tool that has been created in mg/dl units. Before entering the linear equation into coding, the output that appears on the LCD or stored on the SD card is the voltage value in volts. In testing this tool, the value from the glucometer is needed as a reference or standard value. This is done to see the accuracy of the blood sugar level values read on the tool by comparing the results of checking blood sugar levels from the tool with a glucometer. This test is not limited by age, so any age can be tested with this tool.

Collecting data on a non-invasive blood sugar level measuring device requires attention to the position of the patient's finger, because the hole in the finger cannot automatically adjust to the size of the patient's finger, resulting in the position of the finger sometimes being unstable. Because the hole is too large, the tool is calibrated first so that the position of the patient's finger when collecting data can be stable. Position the patient's finger facing and parallel to form a 1800 angle with the photodiode sensor and laser diode. The laser diode will emit light onto the patient's finger and the photodiode sensor will read the voltage value by utilizing optical properties, namely laser absorption of the liquid medium, in this case the patient's blood. Figure 7 shows a comparison of blood sugar level data in mg/dl produced by the device and the glucometer.

Based on Figure 7, the measurement error (discrepancy) value of all data is still below 1 so that the measurement results produced by a non-invasive blood sugar level measuring device are considered good. The average error value produced is 0.0905 or 9.05%. When compared with previous research, it was 1.659%. The smallest measurement error was in patient C and patient Q, namely 0.01 or around 1%, whereas previous research had error values of 1.659% (Nugroho et al., 2021) and 1-15% (Kemalasari & Purnomo, 2011). Because the measurement error value is small, the tool made has high accuracy.

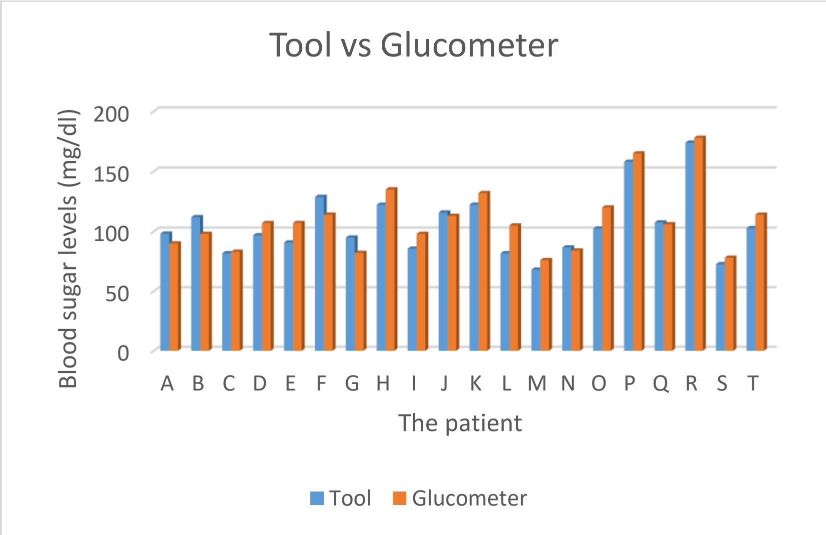

Figure 7 Comparison of blood sugar level values in mg/dl produced by the device and glucometer

Conclusions

This research has successfully created an Arduino-based non-invasive blood sugar measuring device using the linear regression method. The correlation coefficient (r) obtained was 0.971, indicating a very strong relationship between voltage (V) and blood sugar levels (mg/dl). The linear regression equation obtained is y=31.401+36.002x, with an average error value of 0.0905. The smallest measurement error was in patient C and patient Q, at 0.01 or around 1%, while the largest measurement error was in patient L, at 0.22 or around 22%. However, this study has some limitations. Firstly, the finger clamp used may not fit all patients' finger sizes, affecting the stability and position during data collection. Secondly, the sensor used for light intensity readings has limitations in accuracy and sensitivity. Lastly, validation was only performed against a specific glucometer standard, without using laboratory test results for more accurate comparison. Based on these limitations, future research should focus on developing a better finger clamp that adjusts to different finger sizes, improving sensor accuracy and sensitivity, and validating the device with laboratory test results for enhanced performance assessment.

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